

# A Novel Method for Segmentation of Medical Ultrasound Images

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## Abstract

The traditional C-V model had a problem of intensity inhomogeneous in segmentation for images. This paper proposed a modified C-V model based on local gray information, called Local Gray Chan-Vese (LGCV) model, through using local gray image information, this model could segment inhomogeneous image in less number of iterations. Experimental results also prove the effectiveness of this method.

## Keywords

Medical Ultrasound Image; Segmentation; C-V Model; LGCV Model

## Introduction

Ultrasound image segmentation was a typical problem in medical image segmentation due to the poor contrast and gray uneven which were caused by the speckle noise. After decades of development, a lot of methods have been proposed for image segmentation technology. such as, segmentation method based on Region, segmentation method based on Edge, Region segmentation method combined with edge, segmentation method based on Graph cut theory and so on.

At present, geometric active contour model has been widely application. Based on the MS model, Chan-Vese proposed C-V model, which was a segmentation method based on the regional statistical information and without depended on the gradient information of the image and with the advantages of not sensitive to light and noise.

According to the segmentation problems of the gray level uneven image in C-V model, this paper increased local gray level information energy item based on the C-V global energy model. It could better adapt to the characteristics of the uniform and nonuniform gray level image by adjusting the coefficient of the global energy item and the local energy item.

## The Improved C-V Model

### The Local Item and the Regularization Item

For the segmentation of gray level nonuniform image, This paper presented the integration into the local gray level statistical information in the C-V model, which contains the LGCV model of the local energy  $E^L$ .

In the images with intensity inhomogeneity, the uneven grayscale effect was slowly changing, so the gray level kept the uniformity characteristics in a small local region. In this paper, it chose the mean of local gray level distribution as a statistical information, then made difference between the image convolution and the original image, which enhanced the intensity contrast between the target and the background greatly. The regional grayscale average value could be replaced by the local grayscale average value through combining with level set method, and obtained the mathematical expression of  $E^L$ , as follows:

$$E^L(d_1, d_2, C) = \int_{inside(C)} |g_k * u_0(x, y) - u_0(x, y) - d_1|^2 dx dy + \int_{outside(C)} |g_k * u_0(x, y) - u_0(x, y) - d_2|^2 dx dy \quad (1-1)$$

Where  $g_k$  was the average convolution operator with size window of  $k$ ,  $d_1$  and  $d_2$  were the gray level average value in internal and external curve of the difference  $(g_k * u_0(x, y) - u_0(x, y))$  between the image convolution and the original image, respectively.

When the evolution curve approximated the real target edge of the difference image in time, the value of the local energy item would decline rapidly and the solution after the local energy reached minimum was the target contour  $C^*$ .

$$\inf_C (F_1^L(C) + F_2^L(C)) \approx 0 \approx F_1^L(C^*) + F_2^L(C^*) \quad (1-2)$$

Where  $F_1^L(C)$  represented the first item in equation

(1-1),  $F_2^L(C)$  represented the second item in equation (1-1).

It introduced the level set function  $\phi(x, y)$  to equation (1-1), so the local item  $E^L$  could be rewrote as follows:

$$E^L(d_1, d_2, \phi) = \int_{\Omega} |g_k * u_0(x, y) - u_0(x, y) - d_1|^2 H(\phi(x, y)) dx dy + \int_{\Omega} |g_k * u_0(x, y) - u_0(x, y) - d_2|^2 (1 - H(\phi(x, y))) dx dy \quad (1-3)$$

Furthermore, the length penalty item  $L(C)$  was added to  $E^L$  regularization item expression for keeping the smooth of zero level set and avoiding to produce the small and isolated area in the final segmentation result, which also made the curve keeping as short as possible in the evolutionary process. Assumed  $C$  was a smooth and closed plane curve:  $C(p): [0, 1] \rightarrow \Omega$ , parameter  $p \in [0, 1]$ , the length of curve  $C$  could be expressed as follows:

$$L(C) = \int_C dp \quad (1-4)$$

Using the zero level set of level set function instead of the curve  $C$ , thus  $L(C)$  was expressed as follows:

$$L(\phi = 0) = \int_{\Omega} |\nabla H(\phi(x, y))| dx dy = \int_{\Omega} \delta(\phi(x, y)) |\nabla \phi(x, y)| dx dy \quad (1-5)$$

In addition, an energy penalty item was added to the regularization item expression for keeping the level set function approximated the signed distance function. The item was expressed as follows:

$$P(\phi) = \int_{\Omega} \frac{1}{2} (|\nabla \phi(x, y)| - 1)^2 dx dy \quad (1-6)$$

In fact, the energy penalty item  $P(\phi)$  amounted to a measurement to measure the similarity between level set function  $\phi$  and signed distance function, which played a key role in avoiding reinitialized process. And then, obtained the regularization item  $E^R$  which was expressed as follows:

$$E^R(\phi) = \mu \cdot L(\phi = 0) + P(\phi) = \mu \cdot \int_{\Omega} \delta(\phi(x, y)) |\nabla \phi(x, y)| dx dy + \int_{\Omega} \frac{1}{2} (|\nabla \phi(x, y)| - 1)^2 dx dy \quad (1-7)$$

Where  $\mu$  was a parameter of controlling the length penalty item, if  $\mu$  was small relatively, the LGCV model could segment the smaller area object, and vice versa.

### LGCV Model Segmentation Algorithm

LGCV model consisted three parts mainly, the first part was the global energy item which composed of

fidelity item in C-V model, as follows:

$$E^G(c_1, c_2, \phi) = \int_{\Omega} |u_0(x, y) - c_1|^2 H(\phi(x, y)) dx dy + \int_{\Omega} |u_0(x, y) - c_2|^2 (1 - H(\phi(x, y))) dx dy \quad (1-8)$$

The second part was the local gray level item showed in (1-3), it was necessary to choose a appropriate size window  $k$  for the average convolution operator  $g_k$ .

The fidelity item could induce the evolving curve to be close to the target edge quickly, and the local item could constraint the curve to stop at the real edge contour of the object, so the local item should be used combining with the global item. The last, added the regularization item to the model and the total energy function of LGCV model was expressed as follows:

$$E^{LGCV}(c_1, c_2, d_1, d_2, \phi) = \alpha \cdot E^G(c_1, c_2, \phi) + \beta \cdot E^L(d_1, d_2, \phi) + E^R(\phi) \quad (1-9)$$

Where  $\alpha$  and  $\beta$  were two positive parameters for measuring the effect of the global item and the local item. In the actual application process, the value of  $\alpha$  and  $\beta$  should be set according to the gray level distribution of image: (1) For the image with uniform gray level distribution, the value of  $\alpha$  should approximate to  $\beta$ , which meant that the global item and the local item had the same effect; (2) For the image with nonuniform gray level distribution, the value of  $\alpha$  should greater than  $\beta$ , which meant that the effect of the local item was strengthened.

Expansion the equation (1-9) to equation (1-10), as follows:

$$E^{LGCV}(c_1, c_2, d_1, d_2, \phi) = \int_{\Omega} (\alpha |u_0(x, y) - c_1|^2 + \beta |g_k * u_0(x, y) - u_0(x, y) - d_1|^2) H(\phi(x, y)) dx dy + \int_{\Omega} (\alpha |u_0(x, y) - c_2|^2 + \beta |g_k * u_0(x, y) - u_0(x, y) - d_2|^2) (1 - H(\phi(x, y))) dx dy + (\mu \cdot \int_{\Omega} \delta(\phi(x, y)) |\nabla \phi(x, y)| dx dy + \int_{\Omega} \frac{1}{2} (|\nabla \phi(x, y)| - 1)^2 dx dy) \quad (1-10)$$

Where  $c_1(\phi)$ ,  $c_2(\phi)$ ,  $d_1(\phi)$  and  $d_2(\phi)$  were expressed respectively as follows:

$$c_1(\phi) = \frac{\int_{\Omega} u_0(x, y) H(\phi(x, y)) dx dy}{\int_{\Omega} H(\phi(x, y)) dx dy} \quad (1-11)$$

$$c_2(\phi) = \frac{\int_{\Omega} u_0(x, y) (1 - H(\phi(x, y))) dx dy}{\int_{\Omega} (1 - H(\phi(x, y))) dx dy} \quad (1-12)$$

$$d_1(\phi) = \frac{\int_{\Omega} (g_k * u_0(x, y) - u_0(x, y)) H(\phi(x, y)) dx dy}{\int_{\Omega} H(\phi(x, y)) dx dy} \quad (1-13)$$

$$d_2(\phi) = \frac{\int_{\Omega} (g_k * u_0(x, y) - u_0(x, y)) (1 - H(\phi(x, y))) dx dy}{\int_{\Omega} (1 - H(\phi(x, y))) dx dy} \quad (1-14)$$

In the light of the above value obtained of  $c_1, c_2, d_1$  and  $d_2$ , the level set evolving equation of energy functional  $E^{LGCV}$  could be expressed as follows:

$$\begin{aligned} \frac{\partial \phi}{\partial t} = & \delta(\phi)[-(\alpha \cdot (u_0 - c_1)^2 + \beta \cdot (g_k * u_0(x, y) - u_0(x, y) - d_1)^2) \\ & + (\alpha \cdot (u_0 - c_2)^2 + \beta \cdot (g_k * u_0(x, y) - u_0(x, y) - d_2)^2)] \\ & + [\mu \cdot \delta(\phi) \operatorname{div}(\frac{\nabla \phi}{|\nabla \phi|}) + (\nabla^2 \phi - \operatorname{div}(\frac{\nabla \phi}{|\nabla \phi|}))] \end{aligned} \quad (1-15)$$

### The Experimental Results and Analysis

In the LGCV model,  $\beta=1$ , and dynamically adjusted the value of the global item parameter  $\alpha$  according to the actual situation of the image. In the experiment, when  $\alpha < 1$ , it adjusted all the gray level nonuniform images, when  $\alpha=1$ , it adjusted all the gray level uniform images. As similar to  $\alpha$ , the length penalty item parameter was adjustable. In this experiment,  $\mu=0.01 \times 255^2$  corresponded to the small object segmentation, and  $\mu=0.1 \times 255^2$  corresponded to the large object segmentation, so it only adjusted  $\alpha$  and  $\mu$  in the following tests.

Figure 2-1 showed the segmentation results of C-V model and LGCV model to an artificial simulation image respectively. Parameters value in Figure 2-1:  $\alpha=0.1$ ,  $\beta=1$  (LGCV model),  $\lambda_1=\lambda_2=1$ ,  $\mu=0.01 \times 255^2$  (C-V model and LGCV model).

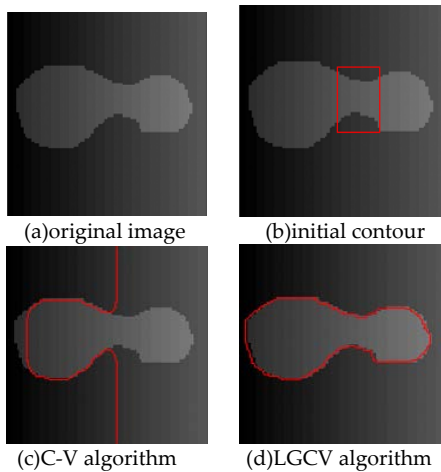


FIG 2-1 SEGMENTATION RESULTS OF SYNTHETIC IMAGE

Figure 2-2 were the medical ultrasound images. For saving operation time, the region of interest in the images should be cut out as the figure 2-3(a) and 2-4(a), and then performed segmentation operation.

Added the energy penalty item to the C-V model in order to the fair comparison, so the C-V model had no

need to reinitialize in the evolutionary process. Parameters value in Figure 2-3:  $\alpha=0.5$ ,  $\beta=1$  (LGCV model),  $\lambda_1=\lambda_2=1$ ,  $\mu=0.01 \times 255^2$  (C-V model and LGCV model).

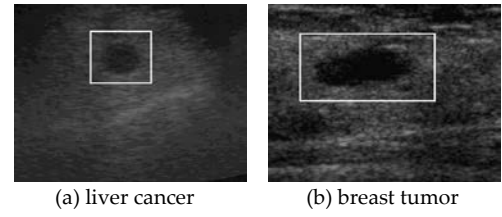


FIG 2-2 CLINICAL ULTRASOUND IMAGES

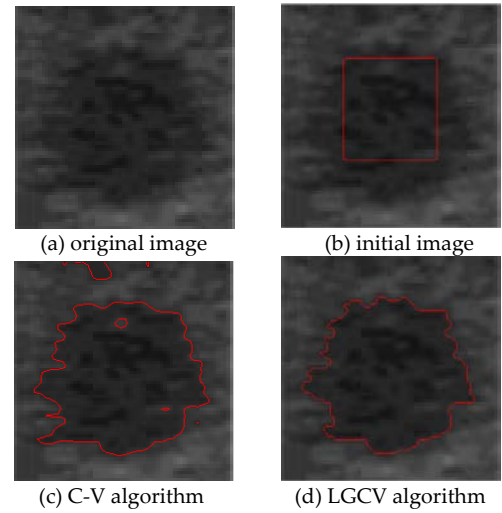


FIG 2-3 SEGMENTATION RESULTS OF LIVER CANCER IMAGE BASED ON CV MODEL AND LGCV MODEL

Parameters value in Figure 2-4:  $\alpha=0.8$ ,  $\beta=1$  (LGCV model),  $\lambda_1=\lambda_2=1$ ,  $\mu=0.1 \times 255^2$  (C-V model and LGCV model).

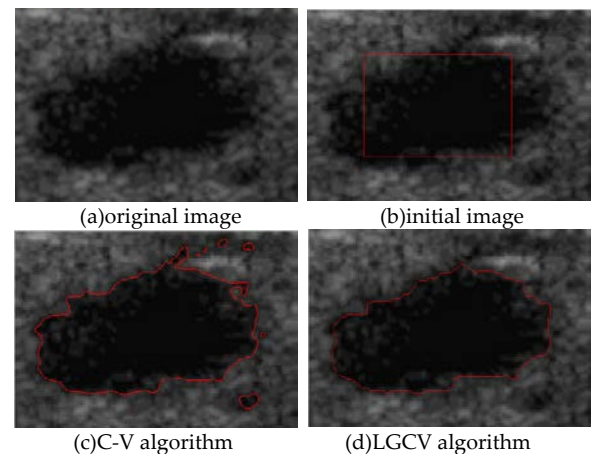


FIG 2-4 SEGMENTATION RESULTS OF BREAST TUMOR IMAGE BASED ON C-V MODEL AND LGCV MODEL

### Conclusions

Based on the C-V model, according to the image segmentation method of using the global information

in C-V model, and regarded the fidelity item of C-V model as the global energy item in the new model, then increased the local gray level information, the local energy item and the regularization item, and finally proposed the improved model, LGCV model. The model could obtain a good segmentation result in gray level uneven image by adjusting the weight of the global item, the local item and the regularization item. Compared to C-V model, the experimental results show that LGCV model has a better segmentation effect in the emulation image and the actual medical ultrasound image with uneven gray level.

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